

## Lecture 17: Markov Chains

### Example:

(a) If today is sunny there is a 70% chance that tomorrow will be sunny.

(b) If today is cloudy the chances are 80% that tomorrow will be cloudy.

Suppose today (Saturday) is sunny what is the probability that next Saturday's weather is also sunny.

### Idea:

Let

$s^{(k)}$  = probability that day  $k$  is sunny

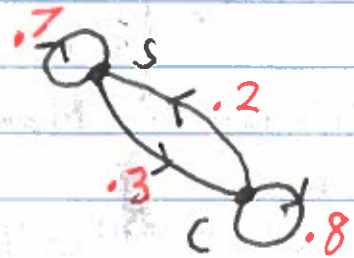
$c^{(k)}$  = probability that day  $k$  is cloudy

### Properties of Probability

$$1. s^{(k)} + c^{(k)} = 1$$

$$2. s^{(k+1)} = .7s^{(k)} + .2c^{(k)}$$

$$c^{(k+1)} = .3s^{(k)} + .8c^{(k)}$$



Let  $\vec{v}^{(k)} = \begin{bmatrix} s^{(k)} \\ c^{(k)} \end{bmatrix}$  it follows that

$$\vec{v}^{(k+1)} = \begin{bmatrix} s^{(k+1)} \\ c^{(k+1)} \end{bmatrix} = \begin{bmatrix} .7 & .2 \\ .3 & .8 \end{bmatrix} \begin{bmatrix} s^{(k)} \\ c^{(k)} \end{bmatrix}$$

$$\begin{array}{cc} & \begin{matrix} s & c \end{matrix} \\ \begin{matrix} s \\ c \end{matrix} & \begin{bmatrix} .7 & .2 \\ .3 & .8 \end{bmatrix} \end{array}$$

transition  
matrix

state vector

Sat:  $\vec{v}^{(1)} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

Sun:  $\vec{v}^{(2)} = \begin{bmatrix} .7 & .2 \\ .3 & .8 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} .7 \\ .3 \end{bmatrix}$

Mon:  $\vec{v}^{(3)} = \begin{bmatrix} .7 & .2 \\ .3 & .8 \end{bmatrix} \begin{bmatrix} .7 \\ .3 \end{bmatrix} = \begin{bmatrix} .55 \\ .45 \end{bmatrix}$

Tue:  $\vec{v}^{(4)} = \begin{bmatrix} .475 \\ .525 \end{bmatrix}$

Wed:  $\vec{v}^{(5)} = \begin{bmatrix} .438 \\ .563 \end{bmatrix}$

Thu:  $\vec{v}^{(6)} = \begin{bmatrix} .419 \\ .581 \end{bmatrix}$

Fri:  $\vec{v}^{(7)} = \begin{bmatrix} .410 \\ .591 \end{bmatrix}$

Sat:  $\vec{v}^{(8)} = \begin{bmatrix} .405 \\ .595 \end{bmatrix}$

The iterates converge fairly rapidly to  $\vec{v}^* = \begin{bmatrix} .4 \\ .6 \end{bmatrix}$  which is called the stationary distribution.

\* Why does this happen??

Definition - A vector  $\vec{v} \in \mathbb{R}^n$  is called a probability vector if each entry  $v_i$  satisfies  $0 \leq v_i \leq 1$  and  $v_1 + \dots + v_n = 1$ .  
( $v_i$  represents probability of being in state  $i$ ).

Definition - A Markov chain is represented by a linear system

$$\vec{v}^{(k+1)} = T \vec{v}^{(k)}$$

satisfying

1.  $\vec{v}^{(1)}$  is a probability vector

2.  $0 \leq T_{ij} \leq 1$ ,

3.  $T_{1j} + T_{2j} + \dots + T_{nj} = 1$ .

( $T_{ij}$  represents probability of transitioning from state  $j$  to state  $i$ )

We call  $T$  a transition matrix.

Theorem - If  $T$  is a transition matrix then there exists a stationary state  $\vec{U}^*$  such that  $T\vec{U}^* = \vec{U}^*$ .

proof:

Let  $M = T^T$ . Therefore,  $M$  and  $T$  have the same eigenvalues and the sum of each row of  $M$  is

Consequently,

$$M \cdot \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} M_{11} + M_{12} + \dots + M_{1n} \\ \vdots \\ M_{n1} + M_{n2} + \dots + M_{nn} \end{bmatrix} = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$$

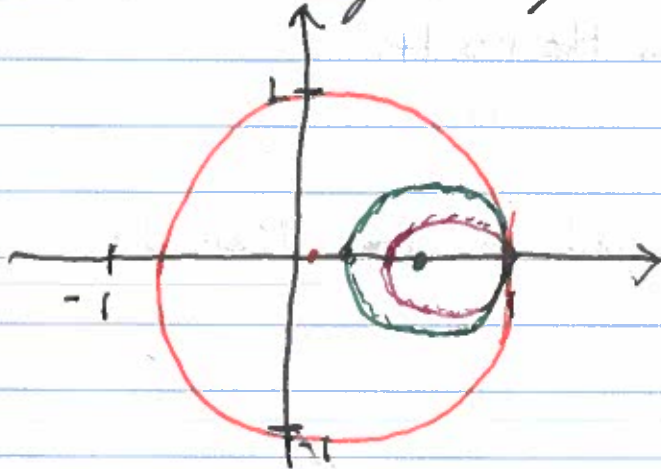
Theorem - The eigenvalues of  $T$  satisfy  $|\lambda_j| < 1$ .

proof:

Let  $M = T^T$ . Each Gershgorin disk satisfies

$$D_i = \{z : |z - M_{ii}| < | - M_{ii} |\}$$

Since the rows of  $M$  add up to one. Consequently, the disks are given by



Theorem - If only one eigenvalue of  $T$  satisfies  $|\lambda| = \lambda^* = 1$

and all other eigenvalues are distinct then

$$\lim_{k \rightarrow \infty} \vec{U}^{(k+1)} = \lim_{k \rightarrow \infty} T \vec{U}^{(k)} = \lim_{k \rightarrow \infty} T^k \vec{U}^{(1)} = \vec{U}^*$$

proof:

Since the eigenvalues of  $T$  are distinct the eigenvectors  $\vec{U}^*, \vec{V}_2, \dots, \vec{V}_n$  with corresponding eigenvalues  $1, \lambda_2, \lambda_3, \dots, \lambda_n$  are linearly independent and thus form a basis. Therefore,

$$\begin{aligned} \vec{U}^{(k+1)} &= T \vec{U}^{(k)} \\ &= T^k \vec{U}^{(1)} \\ &= T^k (c_1 \vec{U}^* + c_2 \vec{V}_2 + \dots + c_n \vec{V}_n) \\ &= c_1 T^k \vec{U}^* + c_2 T^k \vec{V}_2 + \dots + c_n T^k \vec{V}_n \\ &= c_1 \vec{U}^* + c_2 \lambda_2^k \vec{V}_2 + \dots + c_n \lambda_n^k \vec{V}_n. \end{aligned}$$

Taking the limit we have

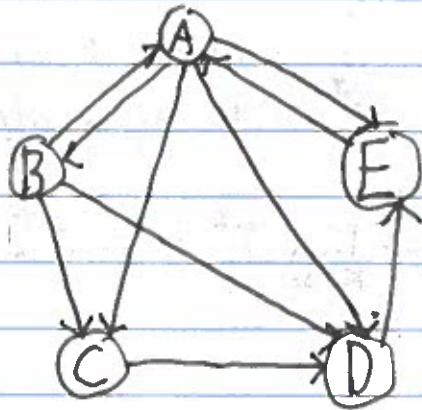
$$\lim_{k \rightarrow \infty} \vec{U}^{(k+1)} = c_1 \vec{U}^*$$

Normalizing, we obtain the result.

(This technique is called the Power Method)

### Example (Page Rank):

Consider the following internet



- On a website A, B, C, D, E each link is followed with equal probability

$$T = \begin{matrix} & \begin{matrix} A & B & C & D & E \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \\ E \end{matrix} & \begin{bmatrix} 0 & \frac{1}{3} & 0 & 0 & 1 \\ \frac{1}{4} & 0 & 0 & 0 & 0 \\ \frac{1}{4} & \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{4} & \frac{1}{3} & 1 & 0 & 0 \\ \frac{1}{4} & 0 & 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

An associated quantity is the adjacency matrix which tracks if nodes are connected

$$A = \begin{matrix} & \begin{matrix} A & B & C & D & E \end{matrix} \\ \begin{matrix} A \\ B \\ C \\ D \\ E \end{matrix} & \begin{bmatrix} 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \end{bmatrix} \end{matrix}$$

Definition - A transition matrix is regular if some power  $T^k$  contains no zero entries, then it is regular.

Theorem - If  $T$  is a regular transition matrix, then it admits a unique stationary probability  $\vec{U}^*$  with eigenvalue  $\lambda=1$ .

Moreover, for all initial states

$$\lim_{k \rightarrow \infty} \vec{U}^{(kn)} = \lim_{k \rightarrow \infty} T \vec{U}^{(k)} = \lim_{k \rightarrow \infty} T^k \vec{U}^{(1)} = \vec{U}^*$$

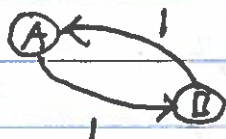
Example:

$$T = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$$T^2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$T^3 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

⋮



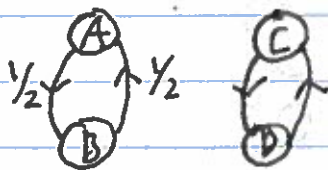
→ Not transitive. No stationary probability

( $T$  is a periodic matrix).

Example:

$$T = \begin{bmatrix} 1/2 & 1/2 & 0 & 0 \\ 1/2 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 1/2 \\ 0 & 0 & 1/2 & 1/2 \end{bmatrix}$$

$$T^2 = \begin{bmatrix} 1/2 & 1/2 & 0 & 0 \\ 1/2 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 1/2 \\ 0 & 0 & 1/2 & 1/2 \end{bmatrix}$$



→ Not transitive

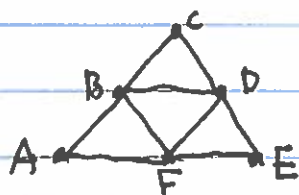
There are three stationary probabilities:

$$\vec{U}_1^* = \begin{bmatrix} 1/2 \\ 1/2 \\ 0 \\ 0 \end{bmatrix}, \quad \vec{U}_2^* = \begin{bmatrix} 0 \\ 0 \\ 1/2 \\ 1/2 \end{bmatrix}, \quad \vec{U}_3^* = \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$$

\* Depending on  $\vec{U}^{(1)}$ , can limit to any of these states.

Example:

An insect crawls along the edges of the following triangular lattice



Upon arriving at a vertex, there is an equal probability of moving to another vertex. Determine, on average, how often each vertex is visited.

The transition matrix is given by

$$\begin{matrix} & A & B & C & D & E & F \\ \begin{matrix} A \\ B \\ C \\ D \\ E \\ F \end{matrix} & \begin{bmatrix} 0 & 1/4 & 0 & 0 & 0 & 1/4 \\ 1/2 & 0 & 1/2 & 1/4 & 0 & 1/4 \\ 0 & 1/4 & 0 & 1/4 & 0 & 0 \\ 0 & 1/4 & 1/2 & 0 & 1/2 & 1/4 \\ 0 & 0 & 0 & 1/4 & 0 & 1/4 \\ 1/2 & 1/4 & 0 & 1/4 & 1/2 & 0 \end{bmatrix} & = A. \end{matrix}$$

Logically, we should be twice as likely to be on vertex B, D, or F than on A, C, or E. If we let  $p$  be probability on corner of triangle then

$$\begin{aligned} 3p + 6p &= 1 \\ \Rightarrow p &= 1/9 \end{aligned}$$

The stationary vector is

$$\vec{v}^* = \begin{bmatrix} 1/9 \\ 2/9 \\ 1/9 \\ 2/9 \\ 1/9 \\ 2/9 \end{bmatrix}$$